

# **Feature Extraction from Hyperspectral Images Compressed Using JPEG-2000 Standard**

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# Acknowledgment

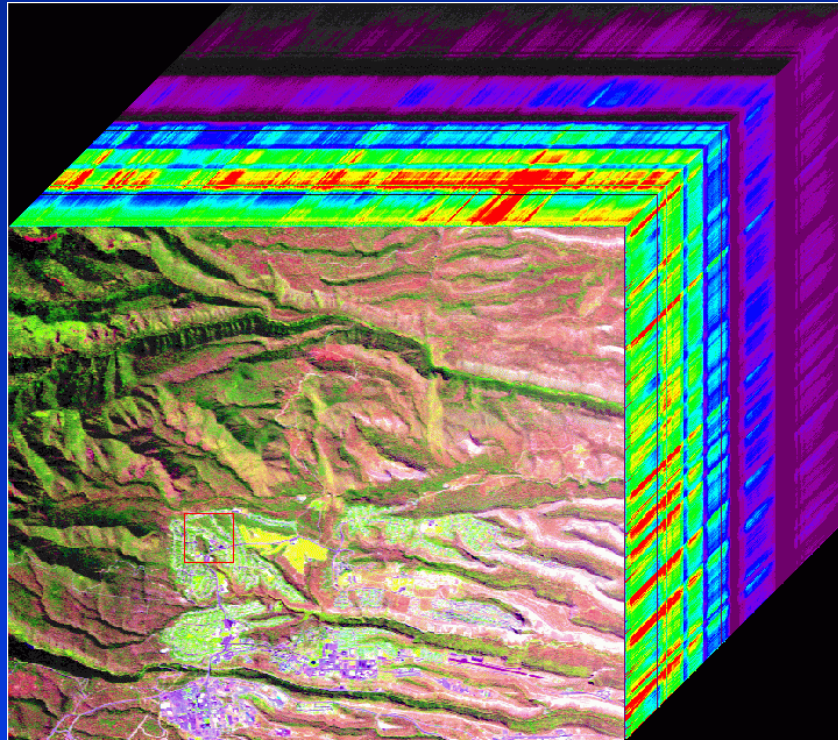
- Thanks to Lee Balick, Jeff Bloch, Chris Borel, Steven Brumby, Anthony Davis, Neal Harvey, John Szimansky, James Theiler.

# Overview

- Feature extraction: preliminaries
- Experiments
- Conclusions

# Hyperspectral Imagery

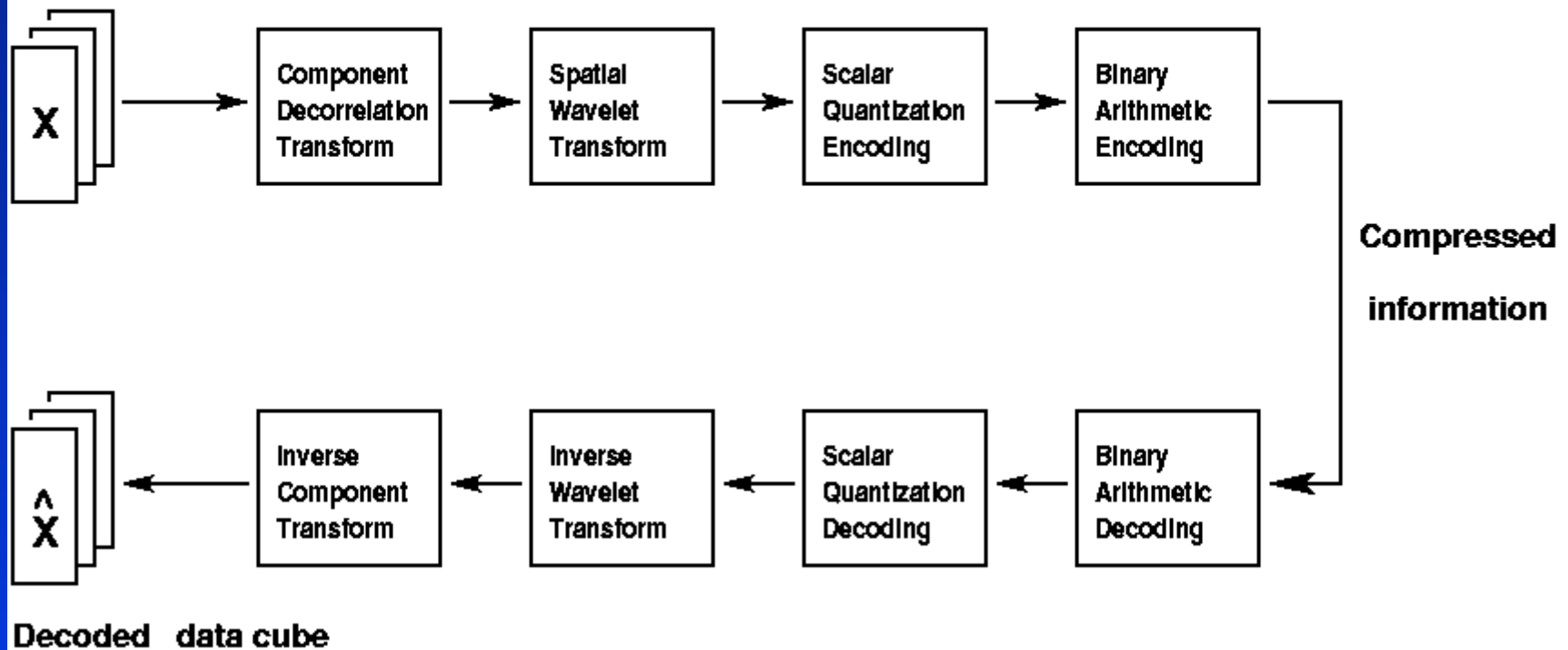
- AVIRIS : Airborne Visible InfraRed Imaging Spectrometer.
- Calibrated images of 224 spectral components (bands).
- Dimensions of an AVIRIS cube: 512 x 614 x 224; 16 bit integer data.
- Los Alamos hyperspectral cube:



# High-Level Overview of JPEG-2000 Standard

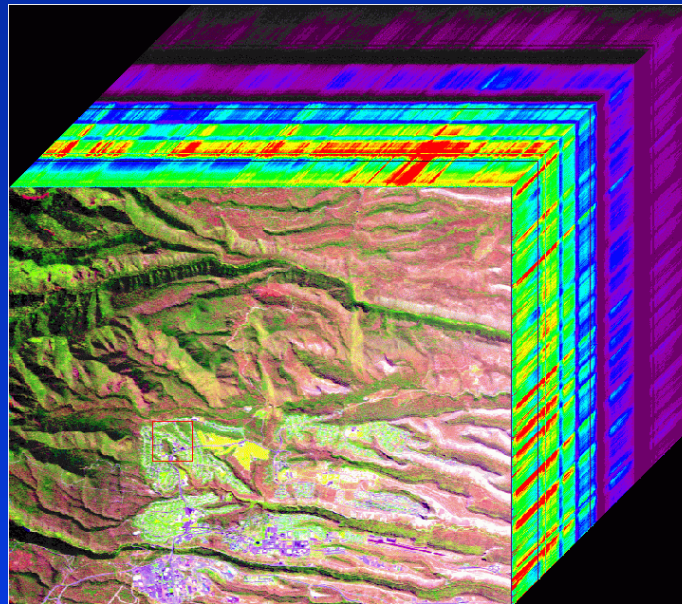
## JPEG – 2000: Compression of Multicomponent Images.

Source data cube

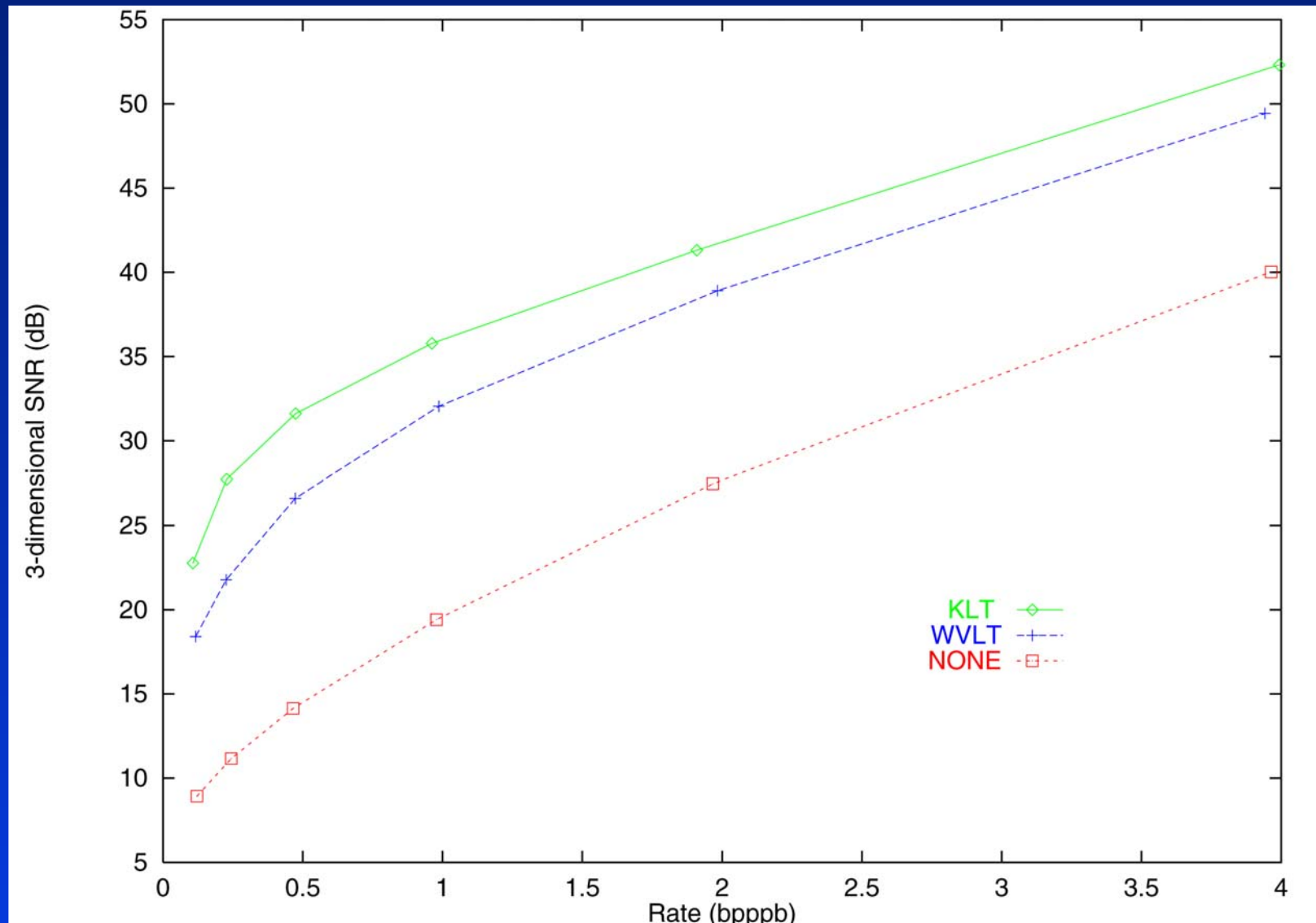


# Data Processing

- Compression/reconstruction using JPEG-2000 standard and various component decorrelations: none, 9x7 Daubechies' wavelet , and Karhunen-Loeve Transform (KLT). Fidelity of reconstructed images is reported as 3-D SNR computed over the whole hyperspectral image cube.
- Feature Extraction tasks: supervised, unsupervised, and hybrid classifications and the transform rendering the Normalized Difference Vegetation Index (NDVI).



# Jasper Rate-Distortion Performance

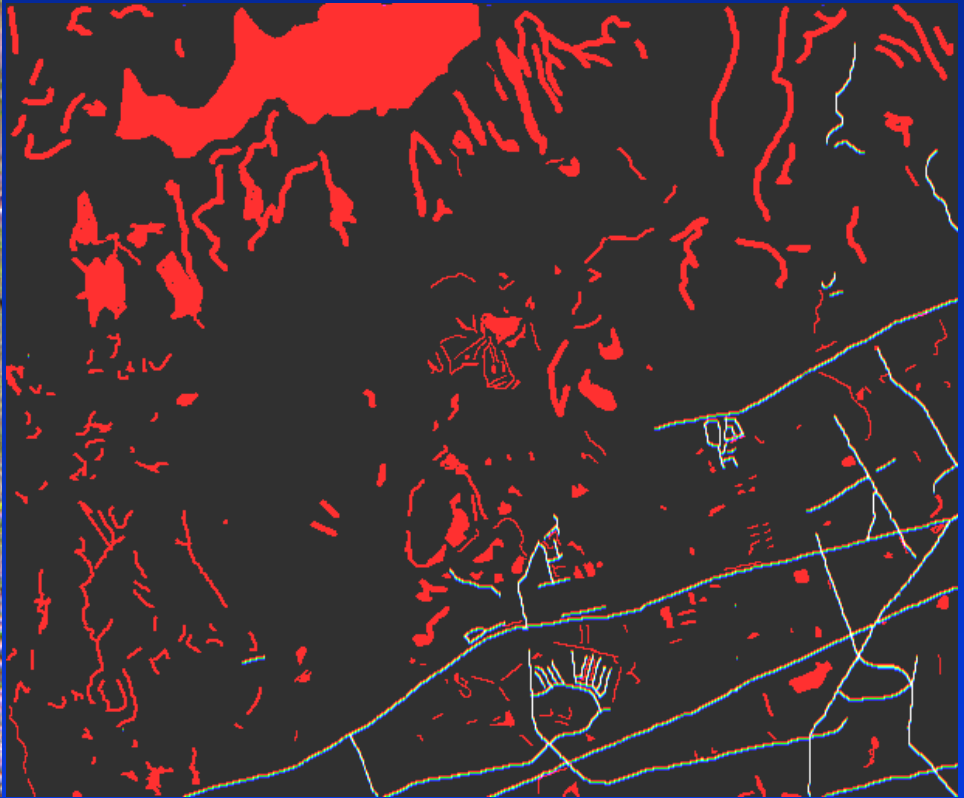
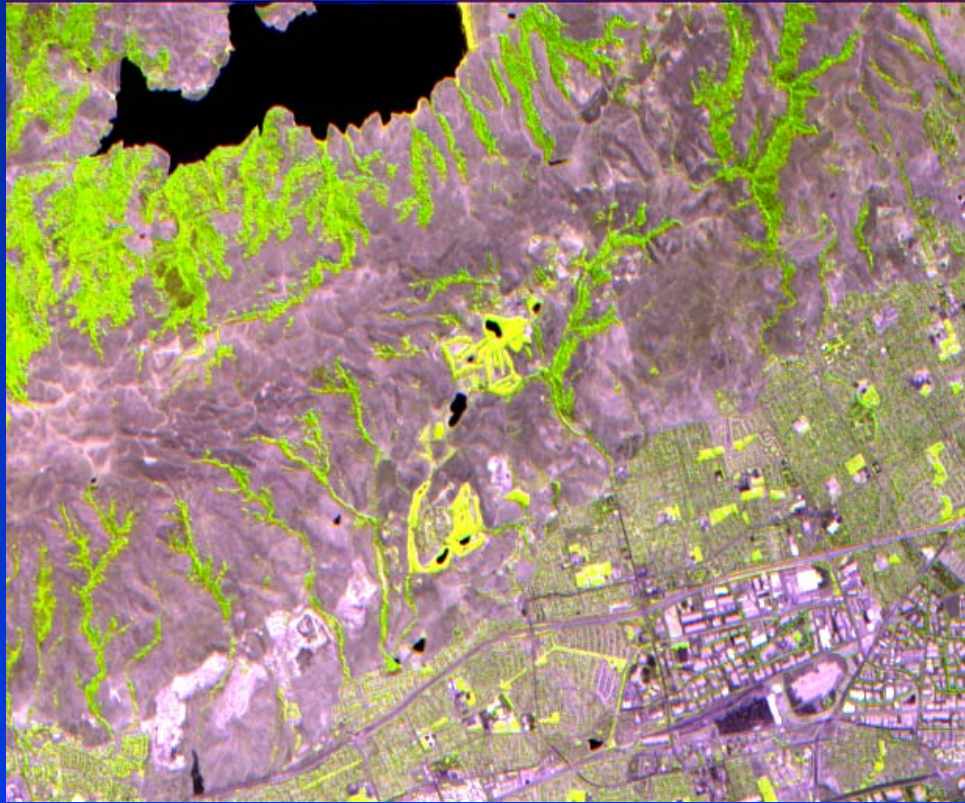




# Moffet Field: The Image and the Training Data

- Source image.

- Training classes. White: asphalt-like; Red: highly different from asphalt.

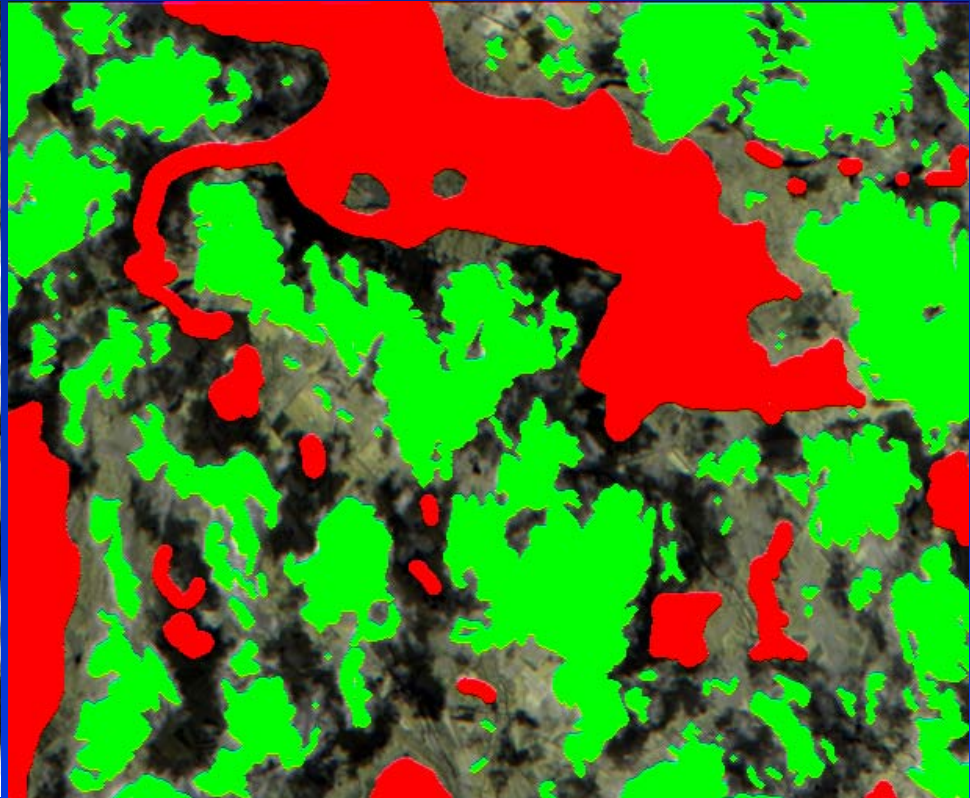
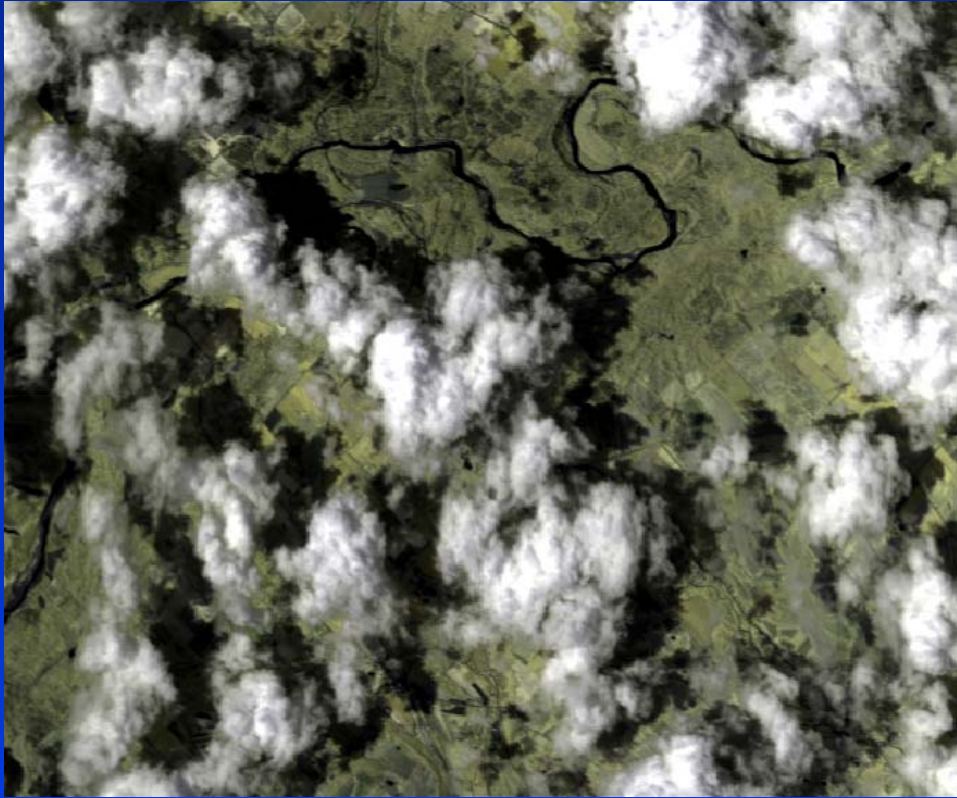




# Clouds: The Image and the Training Data

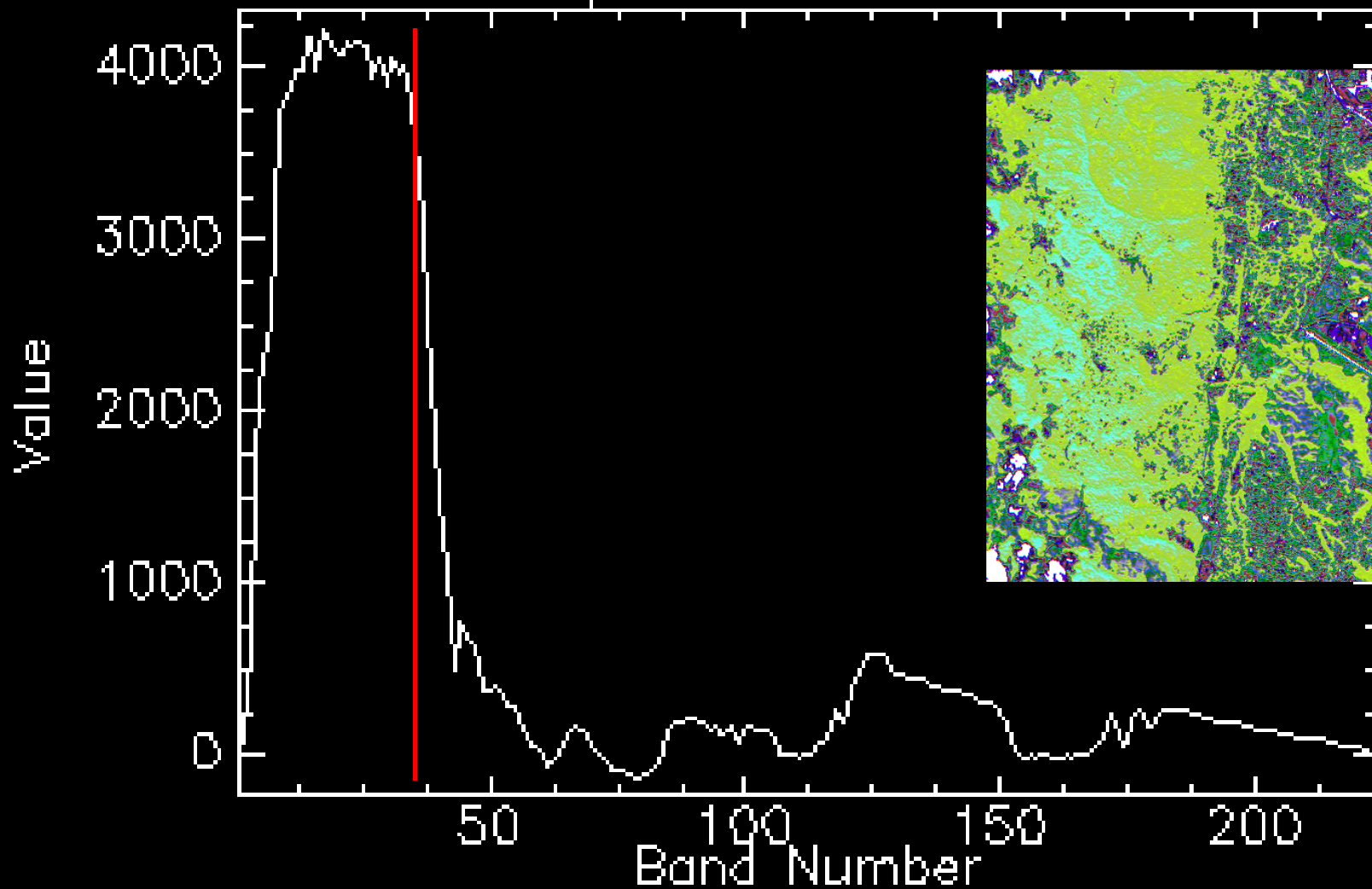
- Clouds data

- Training classes: Green: clouds;  
Red: highly different from clouds.

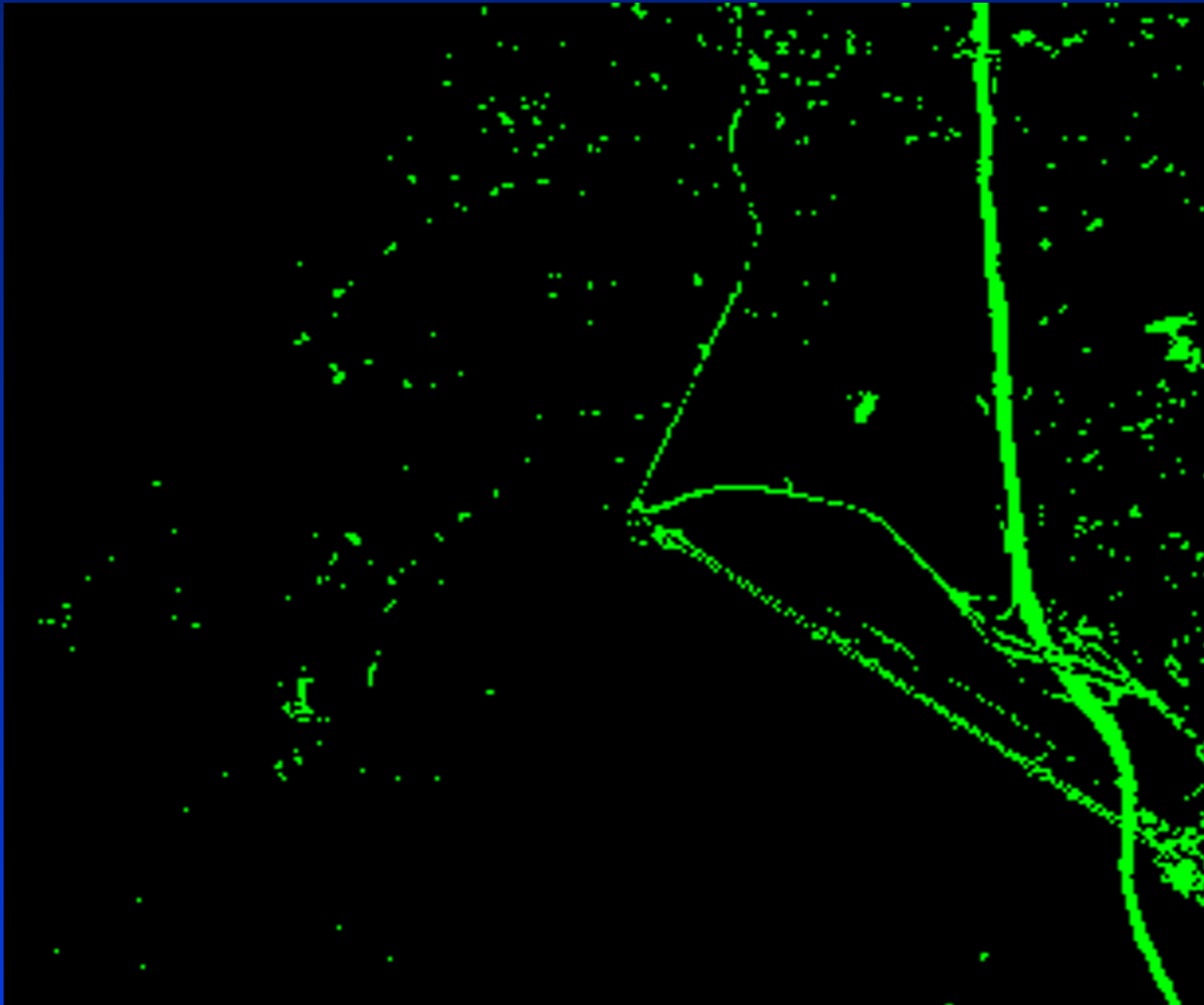


# Jasper Ridge: Image and the “Asphalt-like” Training Class

Spectral Profile



# Thematic Map: Asphalt-like Class



# Feature Extraction Tasks

- All the feature extraction tasks are performed on the original image and on the lossy compressed/reconstructed image
- Based on spectral analysis and spatial analysis (GENIE)
- Supervised Classification: training data is supplied by the analyst
- Unsupervised Classification: no prior information on the data is supplied
- Hybrid Classification: the process starts with the analyst's input and continues automatically
- Normalized Difference Vegetation Index (NDVI)



# Supervised Classifications

- **Spectral Angle Mapper** computes the normalized inner product between training pixels and image pixels. A pixel is assigned to a feature class if the inner product is smaller than a user-supplied threshold.
- **Minimum Distance Classifier** is based on Euclidian distance. A pixel is assigned to a class if the distance to the class mean vector is less than a user-supplied threshold.
- **Binary Encoding:** 1) first every vector (pixel) is quantized to a binary vector by comparison of the pixels' components to its mean: 1 is assigned if the sample is above the vector mean. 2) for each pixel and each (quantized) element of the training class an exclusive OR operation and the Hamming distance are calculated. 3) Classification to a certain class is based on a threshold distance for the Hamming distance.

# Percentage of Pixels Classified Correctly in the Compressed/Reconstructed Images

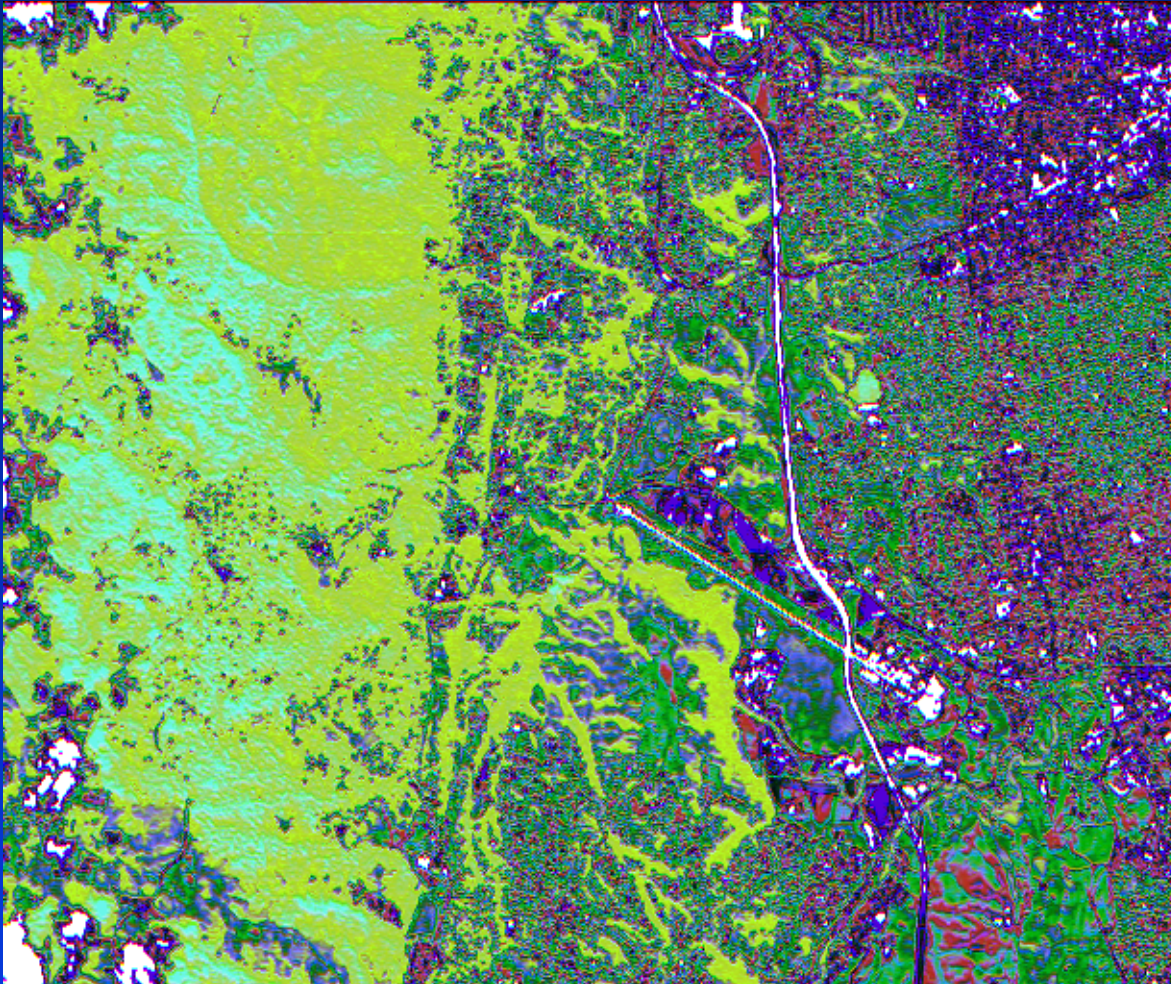
- Assume first that the classification on the original image is correct
- Seek that the classes from the lossy compressed/reconstructed image(s) are the same as the classes on the original image
- Compare the two thematic maps: count the pixels that match



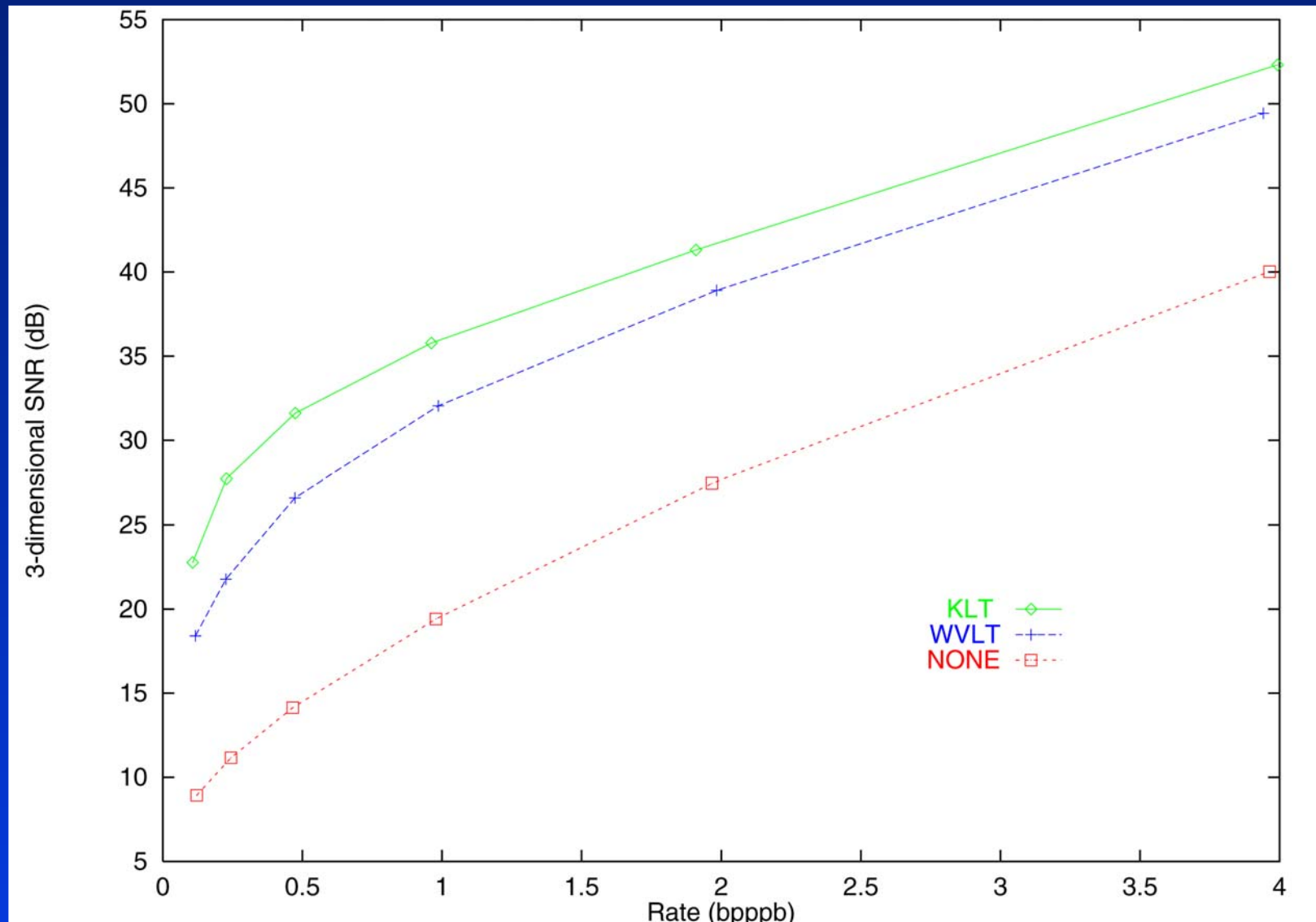
# Percentage of Pixels Classified Correctly in the Compressed/Reconstructed Images

- Assume first that the classification on the original image is correct
- Seek that the classes from the lossy compressed/reconstructed image(s) are the same as the classes on the original image
- Compare the two thematic maps: count the pixels that match
- Classification performance is reported as percentage of “correctly” classified pixels, i.e., percentage of pixels whose classification is the same using both original data and compressed/reconstructed data.

# Jasper Ridge Biological Reserve



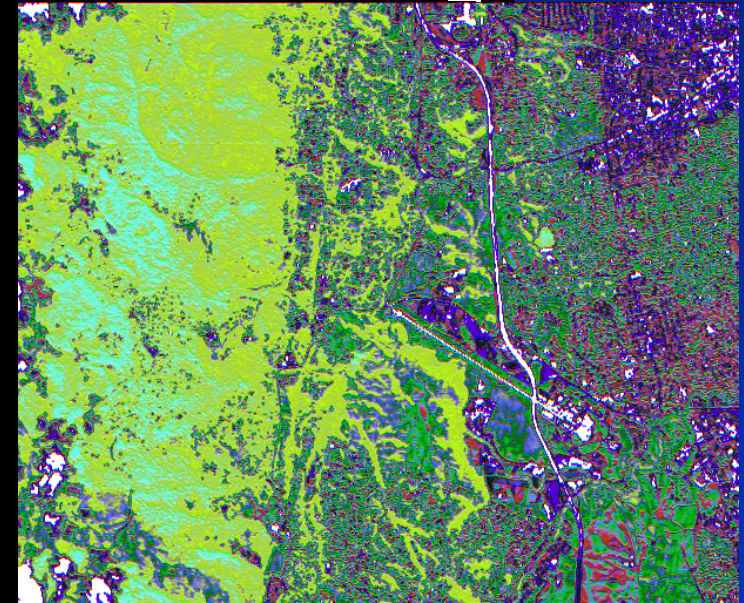
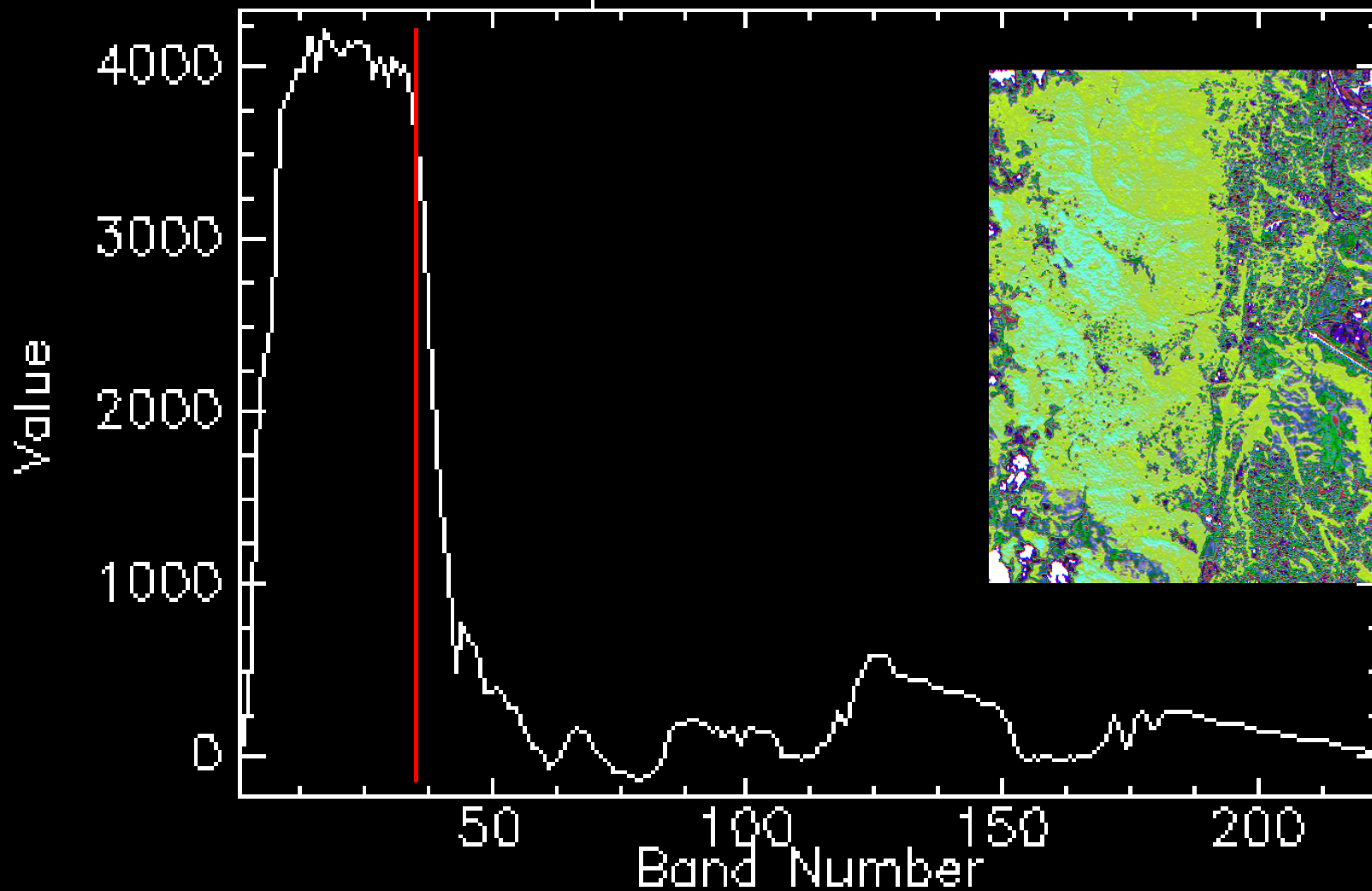
# Jasper Rate-Distortion Performance





# Reference Pixel: “Asphalt-like” for Spectral Angle Mapper Classifier (Training Class)

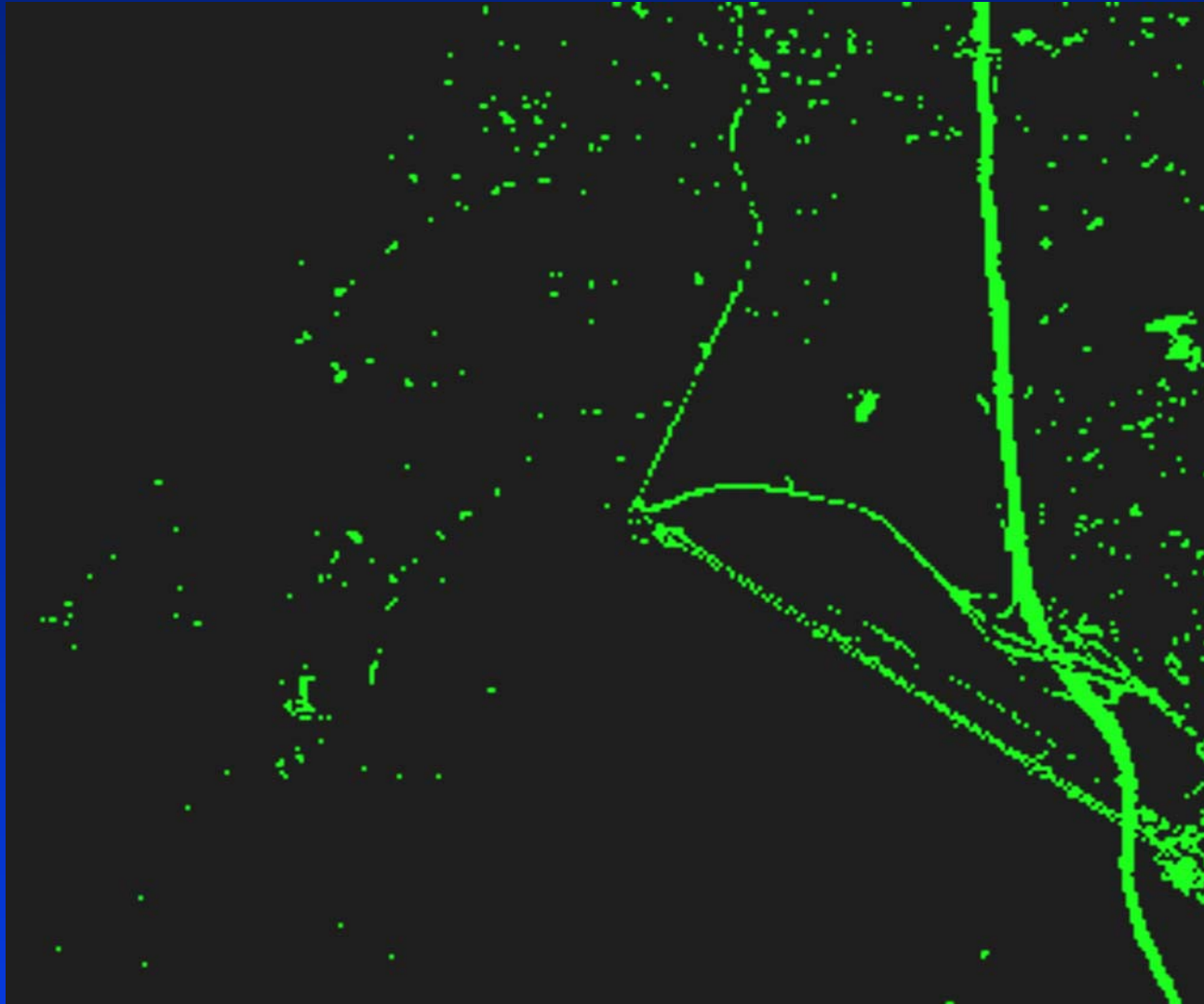
Spectral Profile



# Grayscale Visualization of Spectral Angles



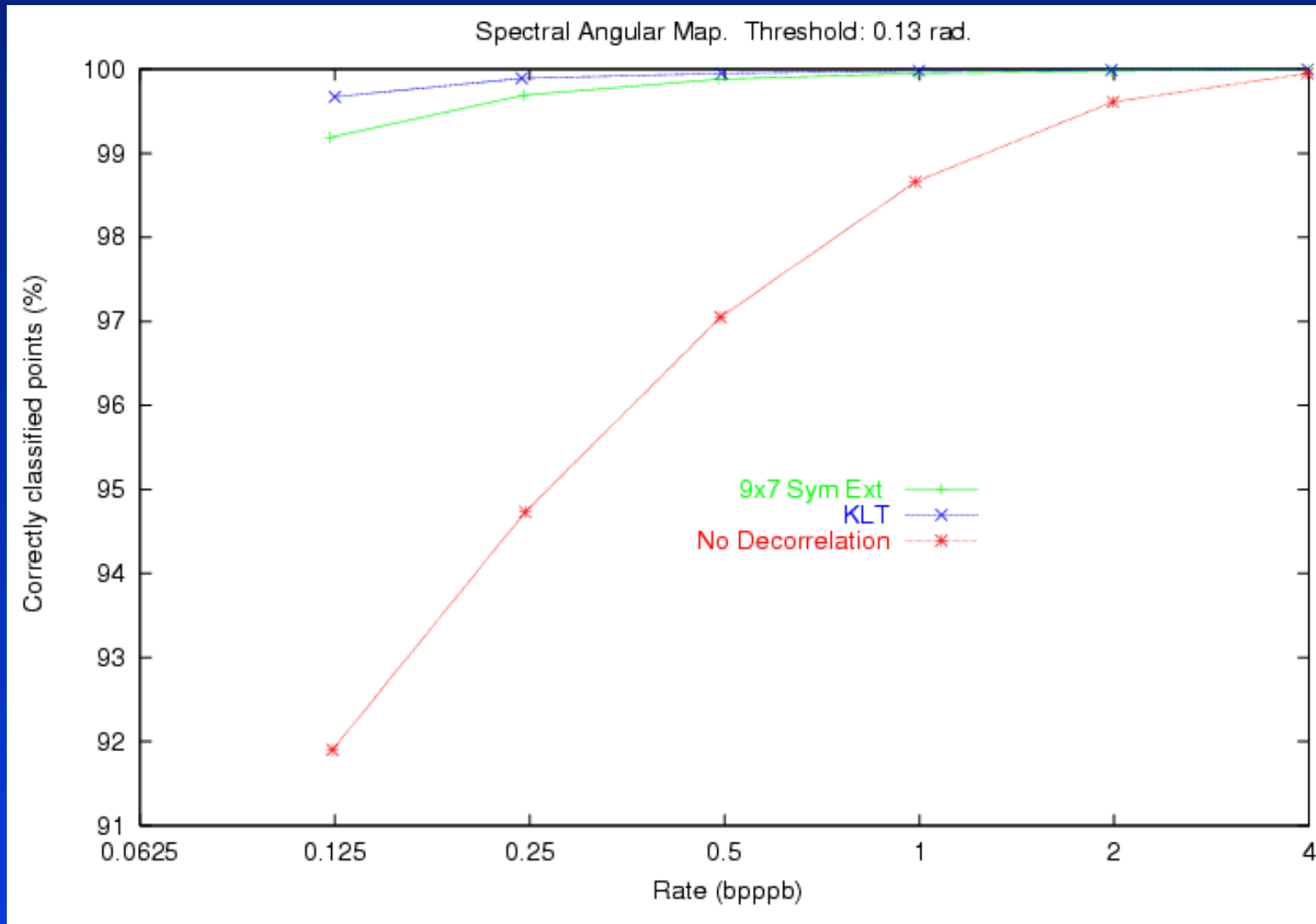
# Asphalt-like Classification with 0.13 rad Threshold





# Jasper Scene. Spectral Angle Mapper Classification.

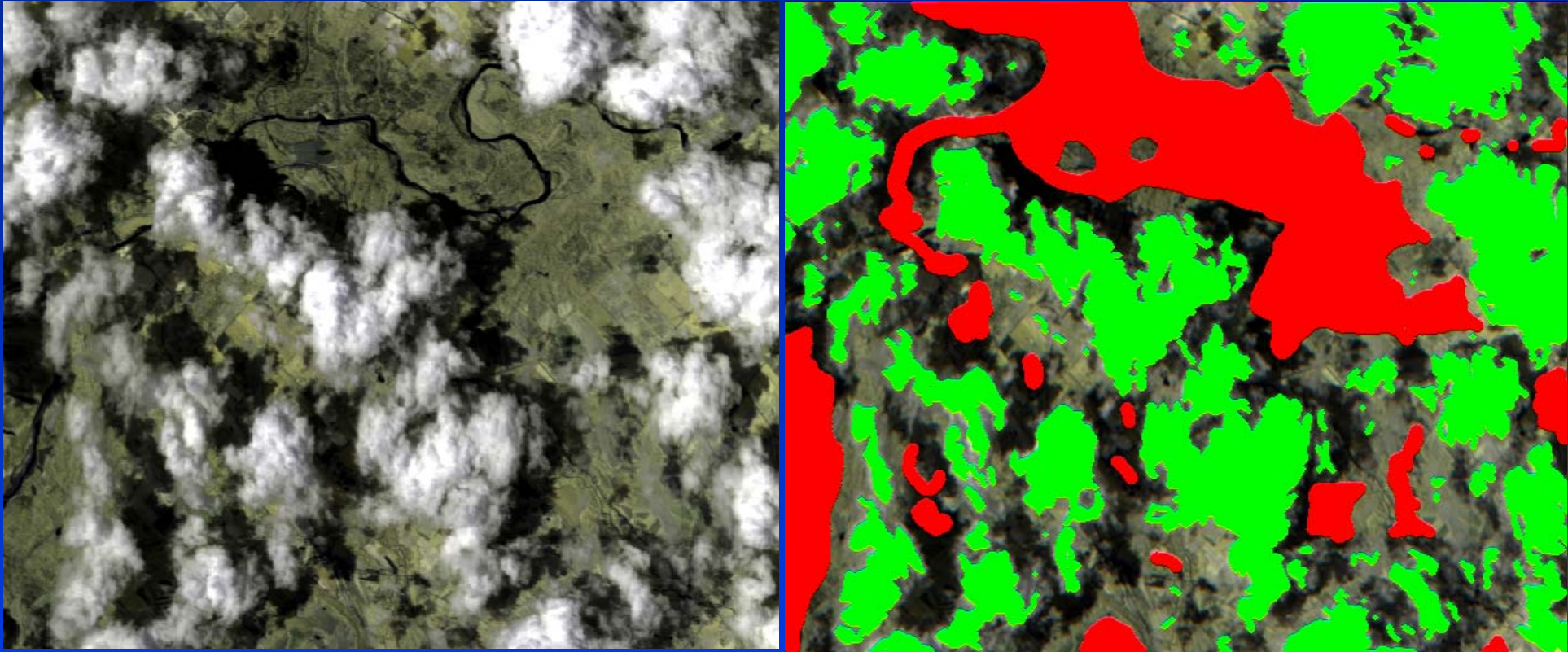
- Percentage of correctly classified points in the Asphalt-like class.



# Clouds: The Image and the Training Data

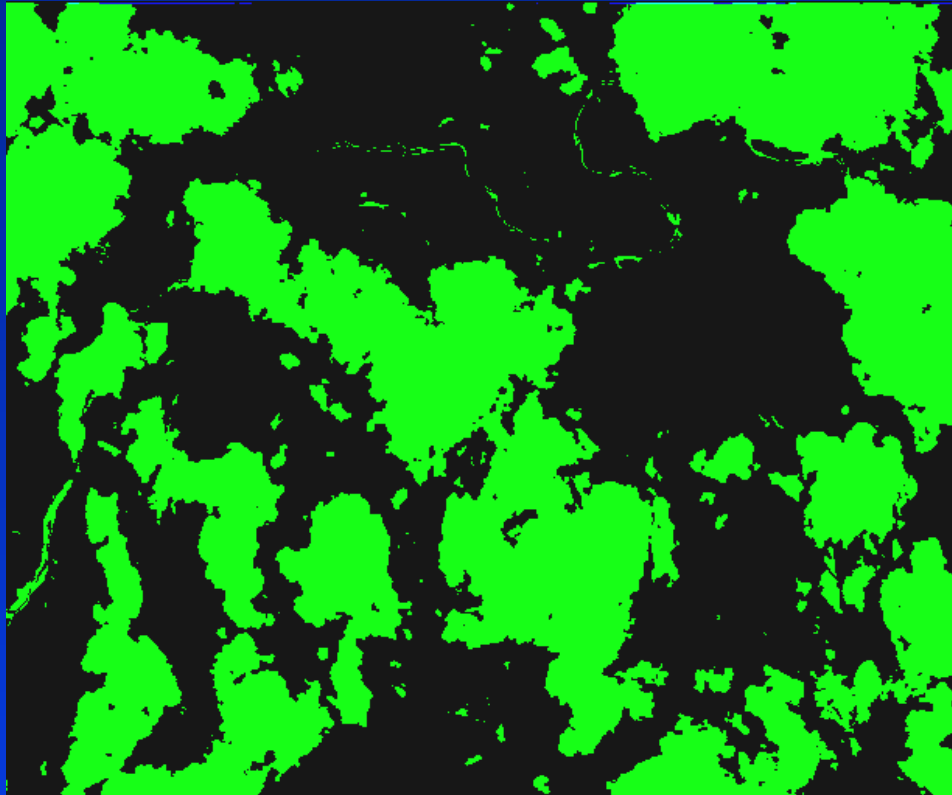
- Clouds data

- Training classes: Green: clouds;  
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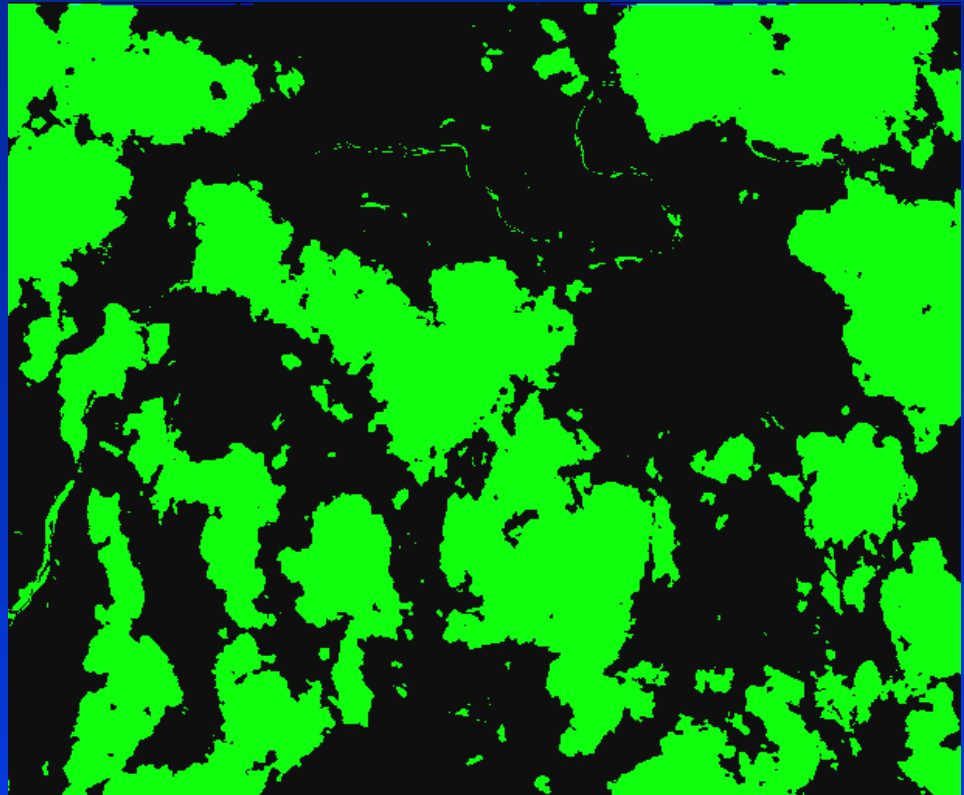


# Clouds. Spectral Angle Mapper Classification.

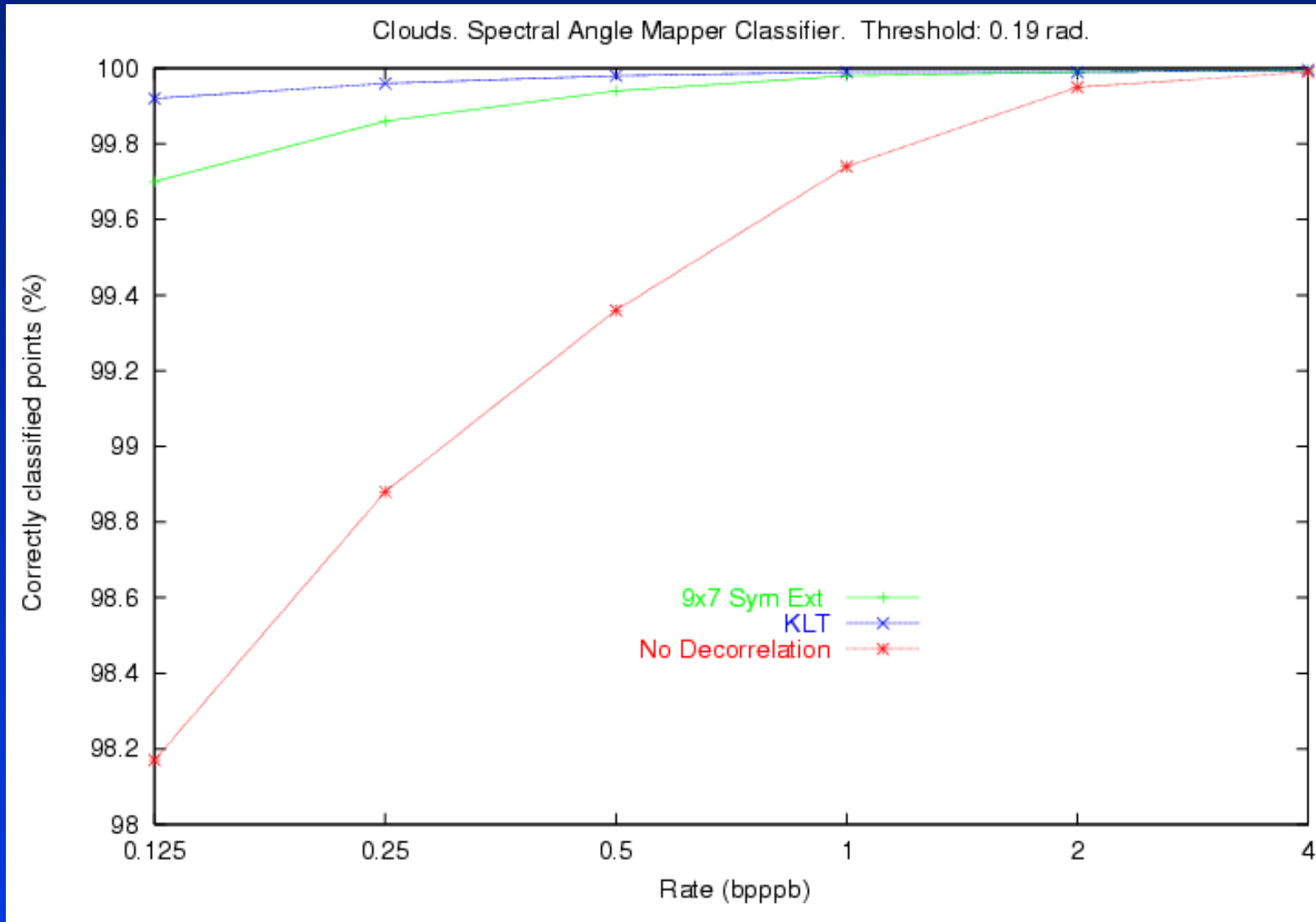
- Classification on uncompressed data



- Classification on compressed/reconstructed data at 0.125 bpppb

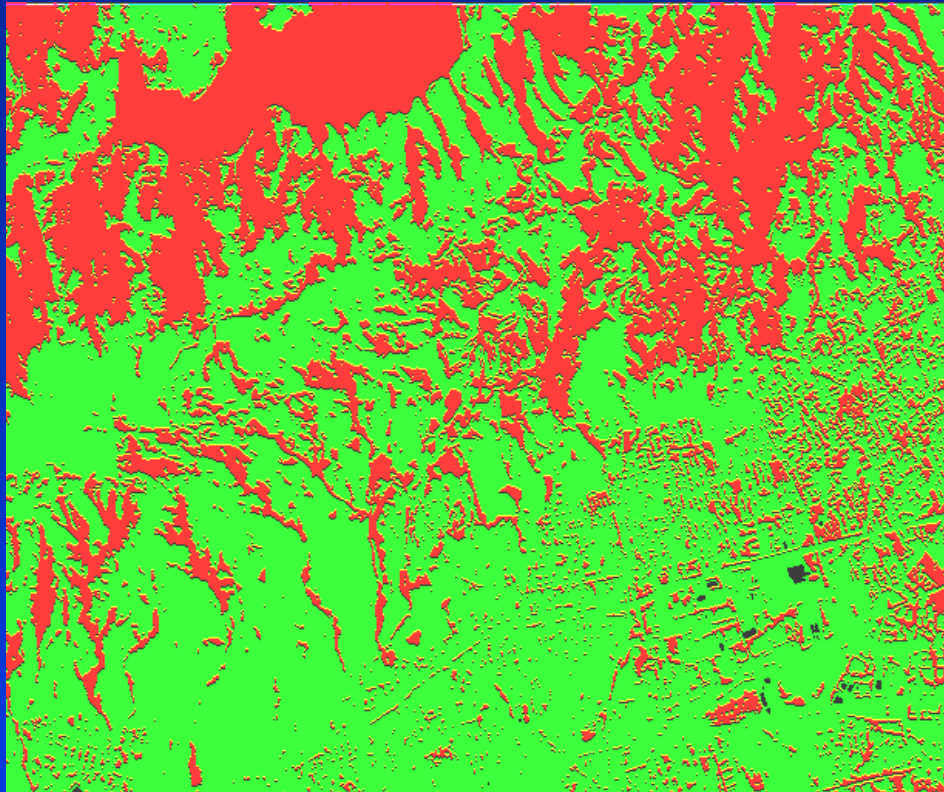


# Clouds. Spectral Angle Mapper Classification. Percentage of correctly classified points.

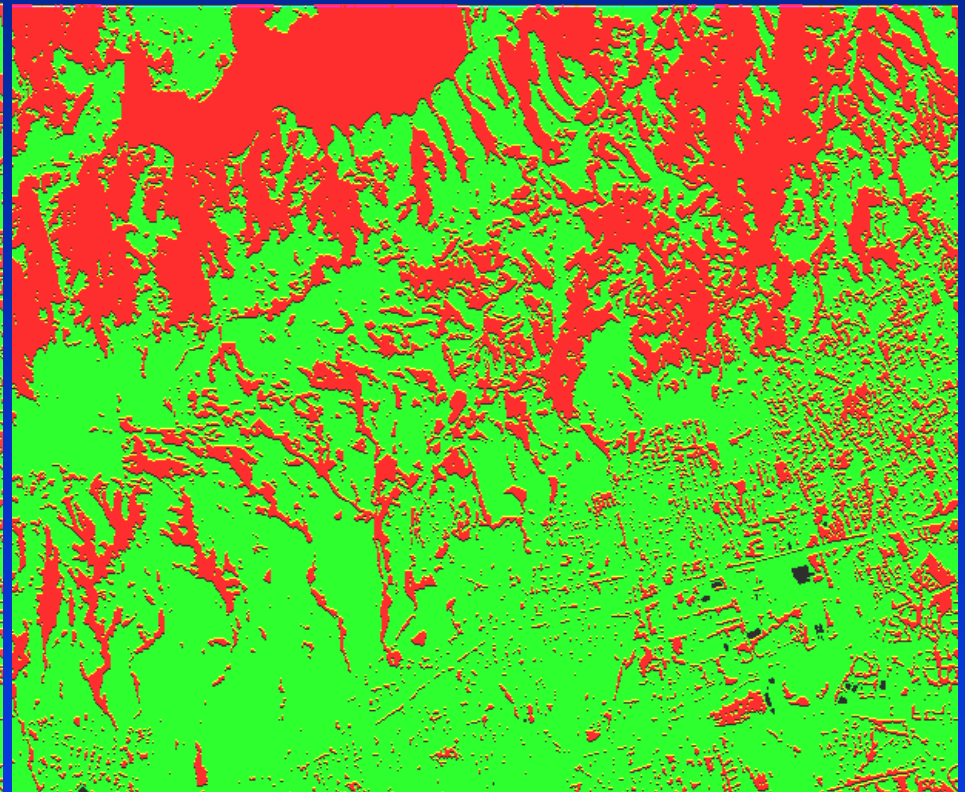


# Moffet Field. Minimum Distance Classifier.

- Classification of the uncompressed image.

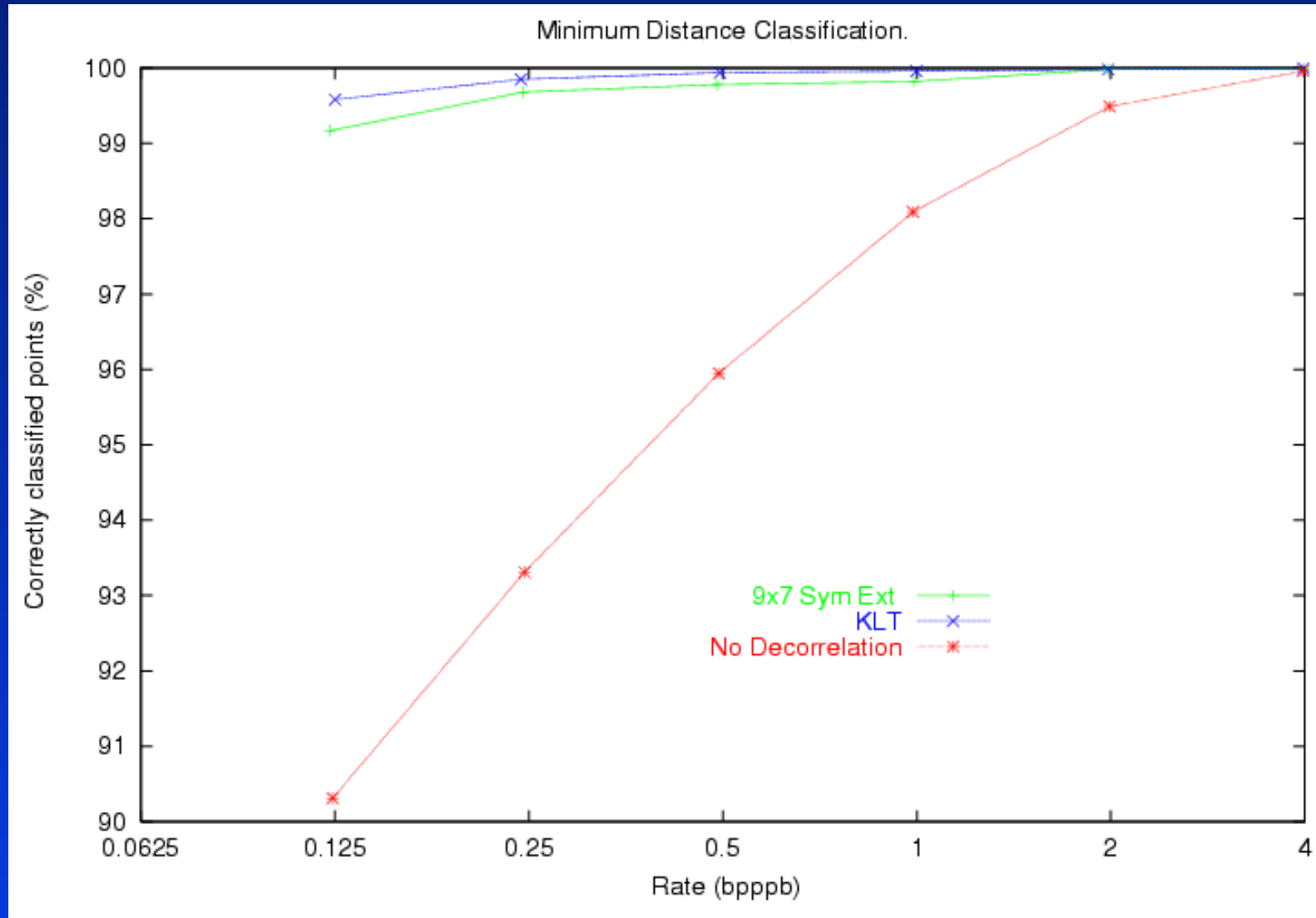


- Classification of the compressed/reconstructed image at 0.125bpppb with KLT decorrelation.



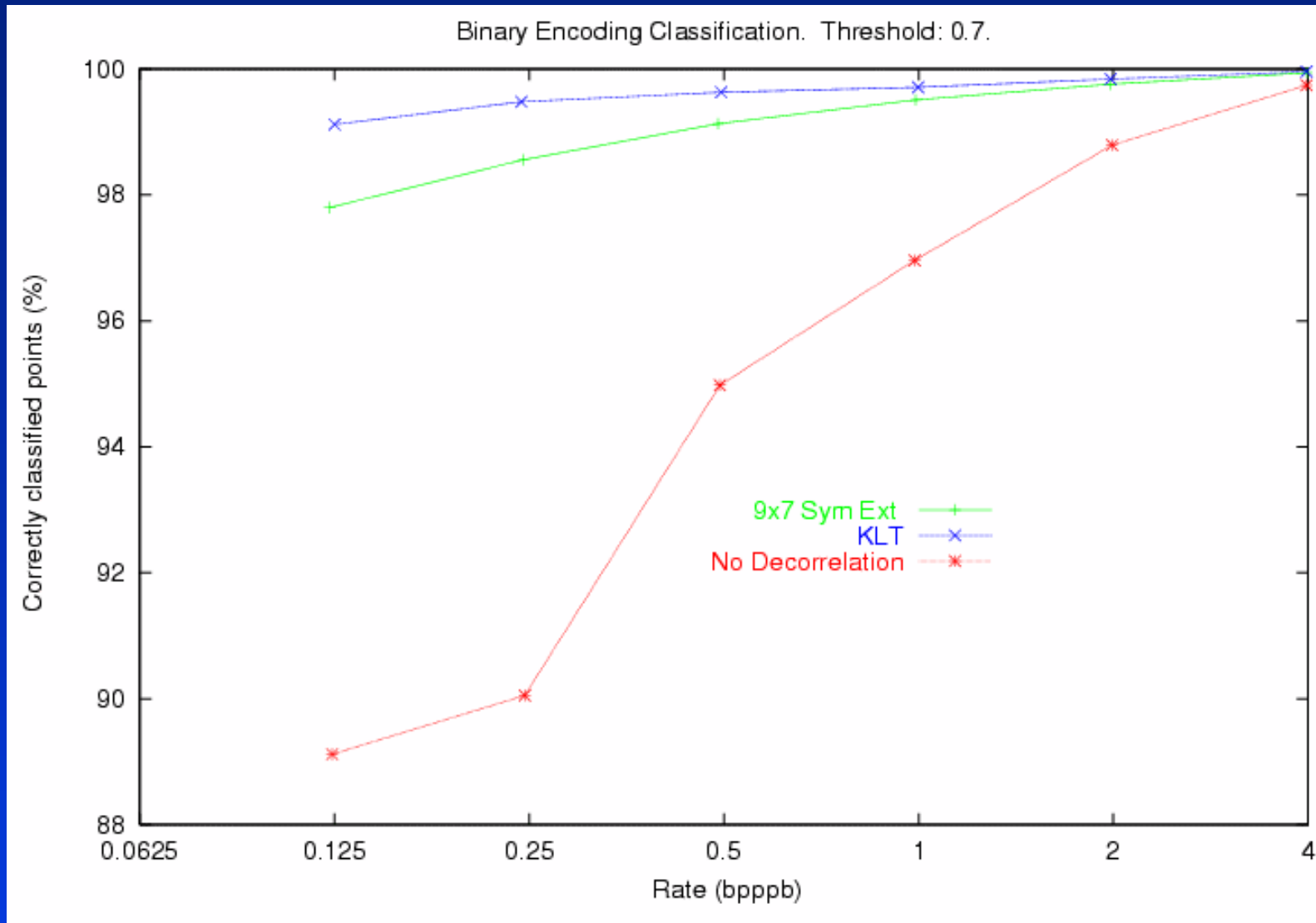


# Moffet Field. Minimum Distance Classification. Percentage of correctly classified points in the Asphalt-like class.





# Moffet Field. Binary Encoding Classification. Percentage of correctly classified points in the Asphalt-like class.



# Unsupervised K-means Clustering Classification

- The user supplies the number of feature classes.
- The process starts with a number of evenly distributed class mean vectors, one per desired feature class.
- Pixels are clustered using a minimum distance criterion
- Iteratively the vector means is recalculated and pixels are reclassified based on their distance to the new mean vectors
- The classification stops when either a user supplied number of iterations took place or when the number of pixels reassigned is less than a specified percentage threshold.

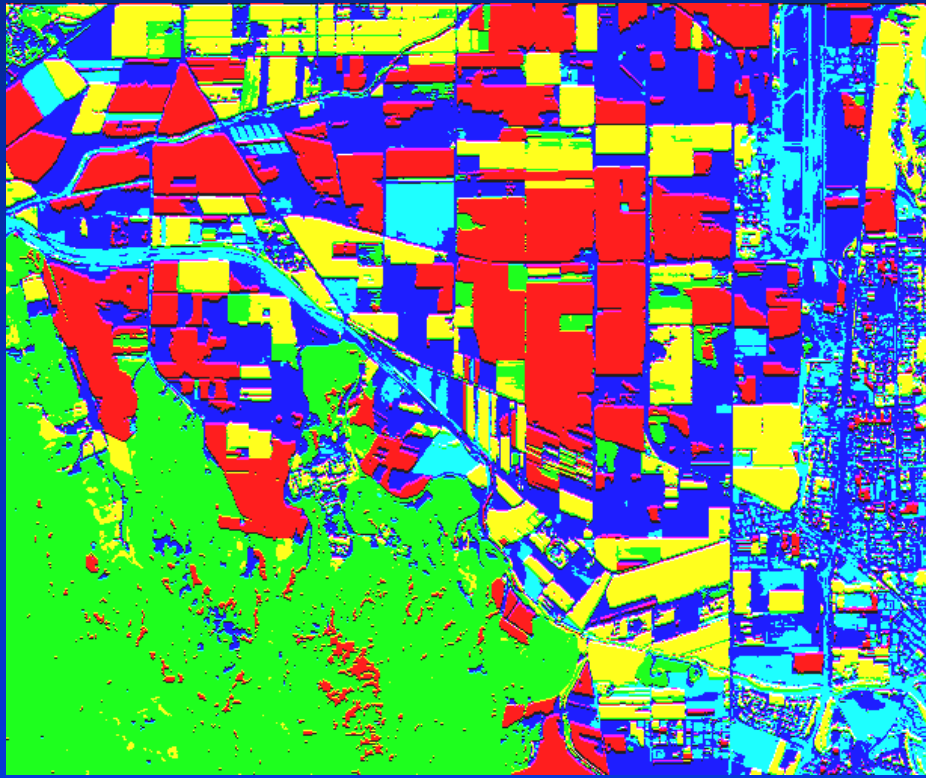
# Camarillo, CA AVIRIS data

- Data used in Imaging Spectroscopy of Water Vapor and Atmospheric Gases.

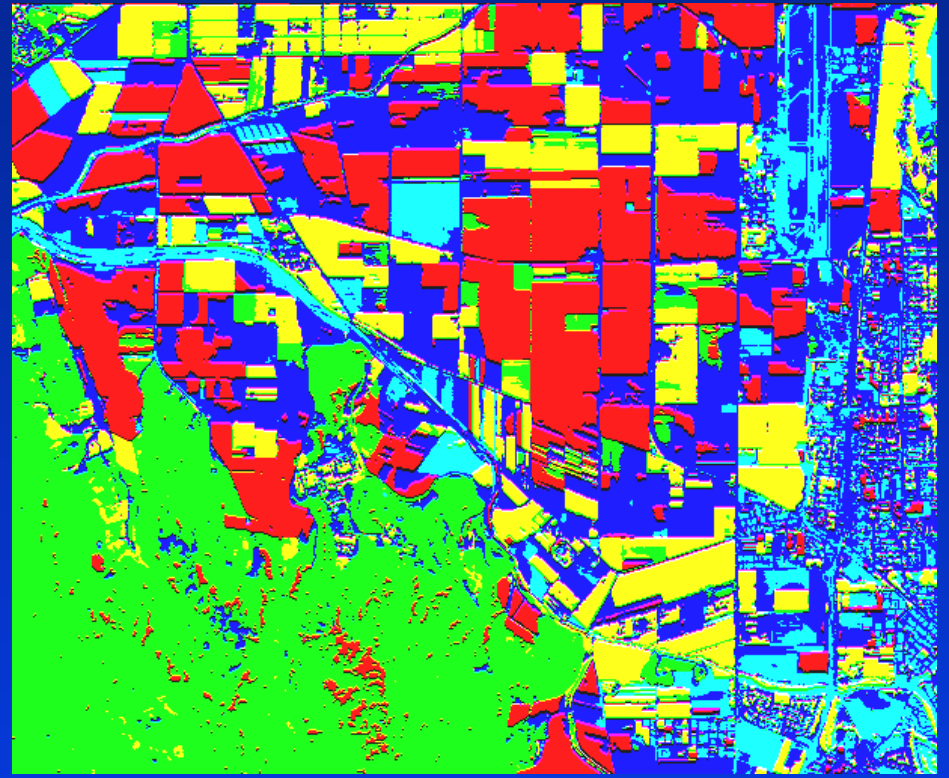


# K-means classification: 5 classes, 5 iterations

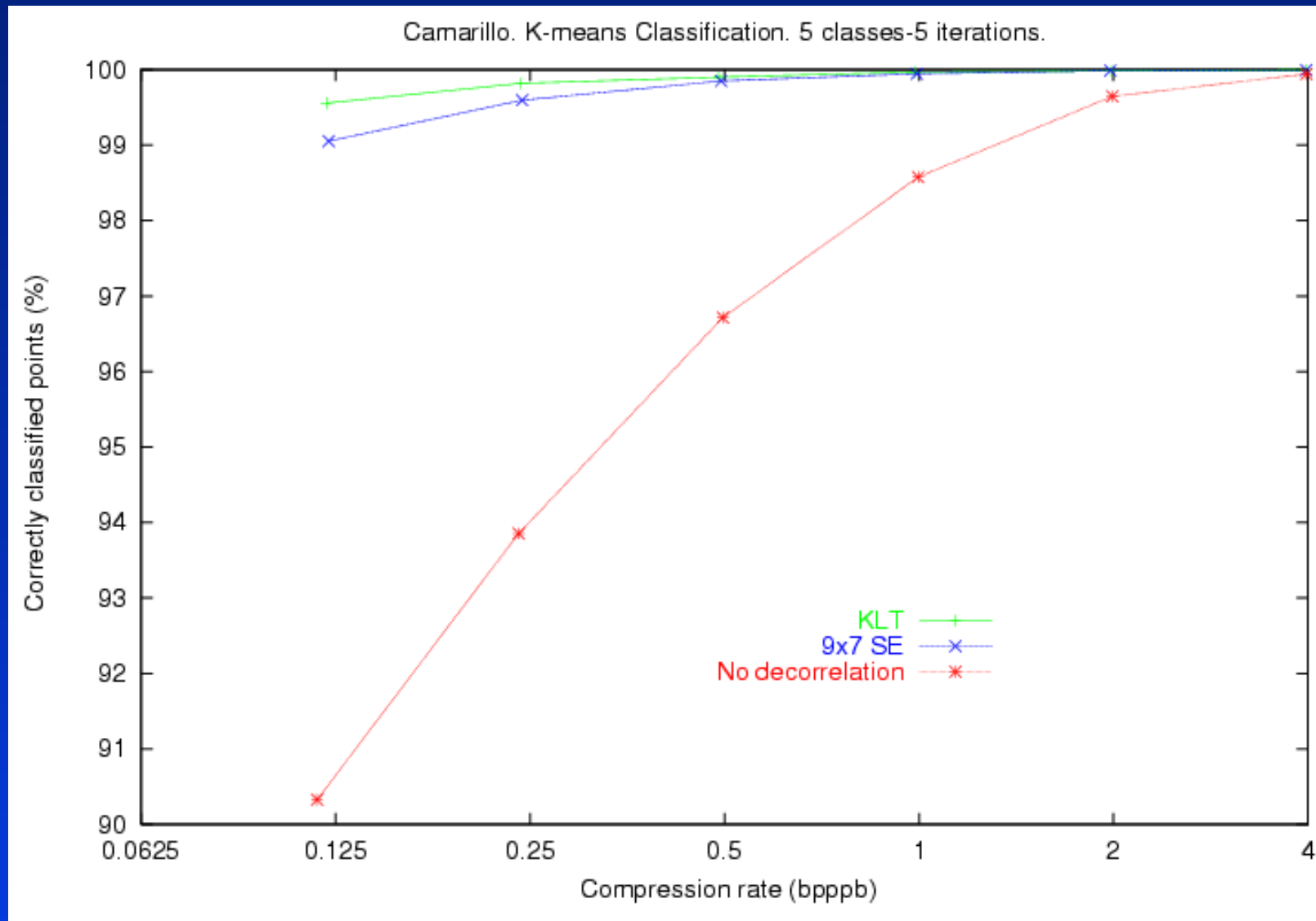
- Classification of the uncompressed image



- Classification of the compressed/reconstructed image at 0.125 bppb



# Percentage of correctly classified points. K-means classification; 5 iterations, 5 classes



# Normalized Difference Vegetation Index Transform

- The Normalized Difference Vegetation Index is a component transform that produces a single 2-D band that represents the vegetation distribution.
- For AVIRIS data, as well as other widely used hyperspectral data types, the NDVI index is the ratio between the difference and the sum of near infra-red and red bands, i.e.:
- $NDVI = (NIR - Red) / (NIR + Red)$
- The values of the NDVI band are between -1 and 1
- Qualitative results are reported in terms of the 2-D SNR of the NDVI field derived from reconstructed image.



# Vegetation index (NDVI Transform)

- NDVI Transform of uncompressed image.

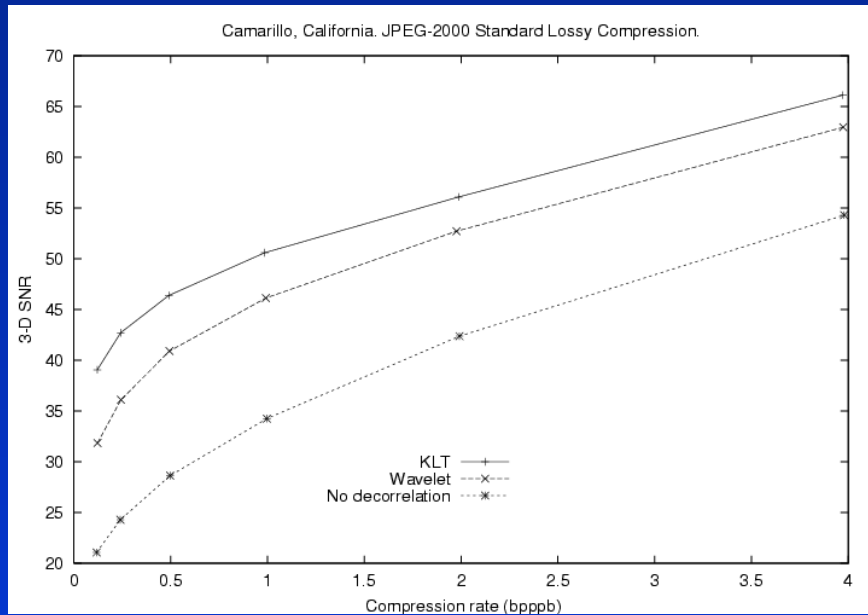


- NDVI Transform of compressed/reconstructed image at 0.125bpppb with wavelet decorrelation.

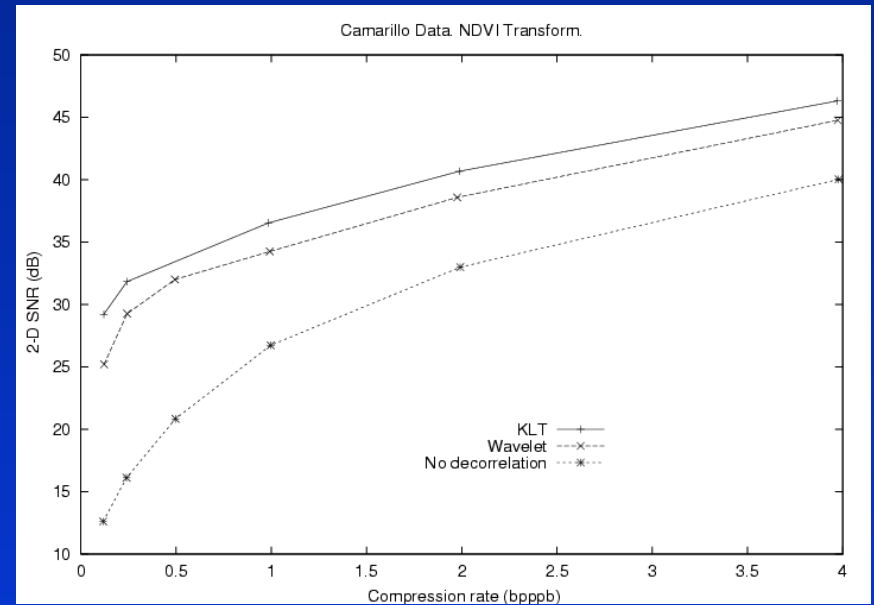


# Similar rate-distortion curves – Camarillo Scene

- Rate-distortion performance (3-D SNR)



- 2-D SNR for NDVI feature



# GENIE (GENetic Imagery Exploitation)

- GENIE is a hybrid evolutionary algorithm. GENIE selects first from the space of the image processing algorithms a set of operations that transform raw image planes into new components (feature space); these intermediate feature components are then input to a conventional supervised classification technique.
- The training data for GENIE is selected using ALADDIN, a Java-based tool which assists the analyst in marking out and making judgments about features in the data.
- There are only binary-valued training data: true and false. Pixels within the training image not labeled are not considered in the fitness analysis (GENIE supports more than two training classes per data set).

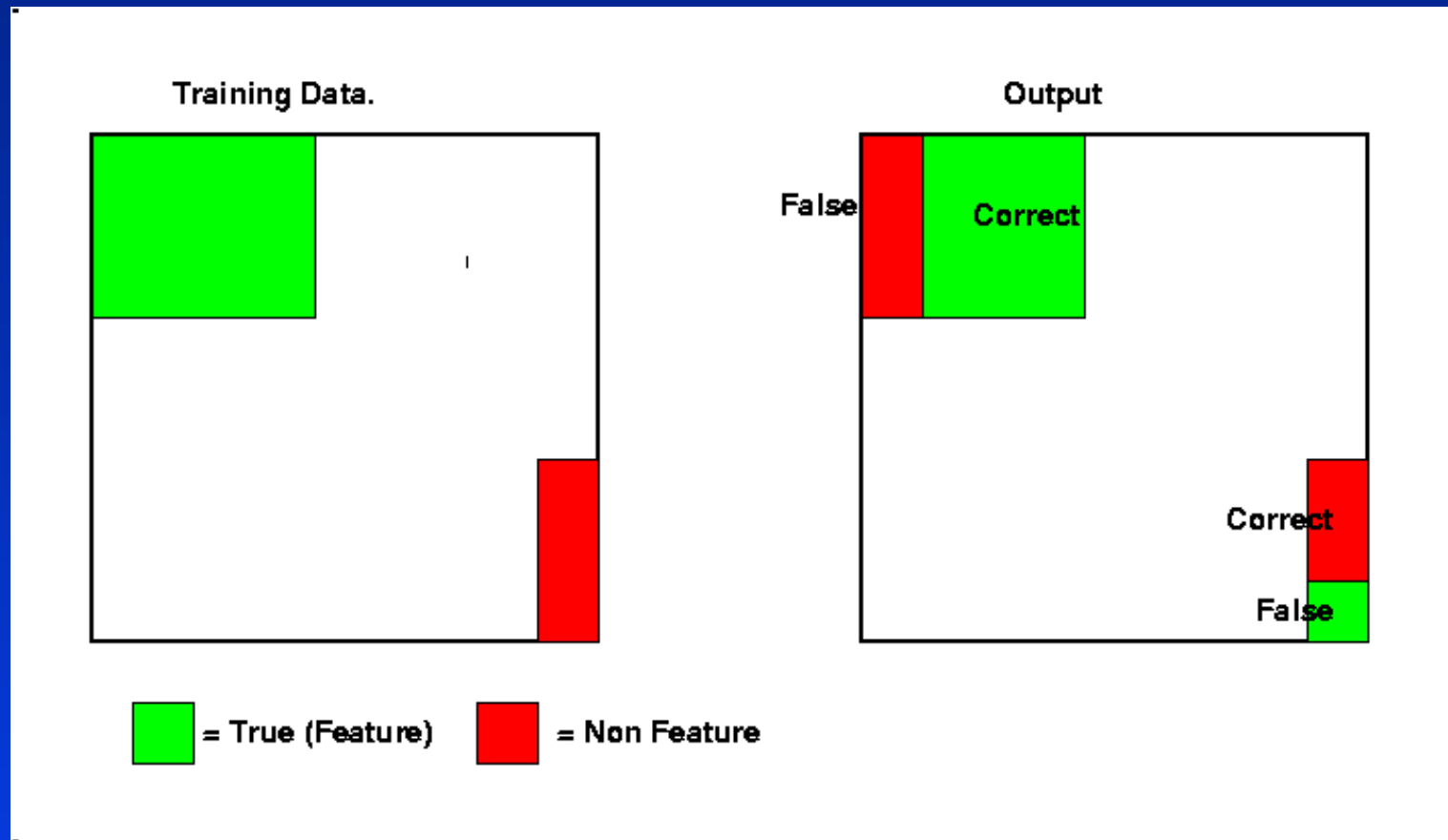
# GENIE's Fitness Evaluation.

- The fitness of a candidate solution is given by the degree of agreement between the final binary output component and the training data (weighted Hamming distance between the output of the algorithm and the training data).
- The fitness rate:  $F = 500 ( R_d + ( 1 - R_f ) )$  where  $R_d$  is the fraction of feature pixels classified correctly over the entire scene and  $R_f$  is the false alarm rate, i.e., the fraction of the non-feature pixels classified incorrectly. A fitness rate of 1000 indicates a “perfect” classification.
- GENIE performance is reported as fitness rate.



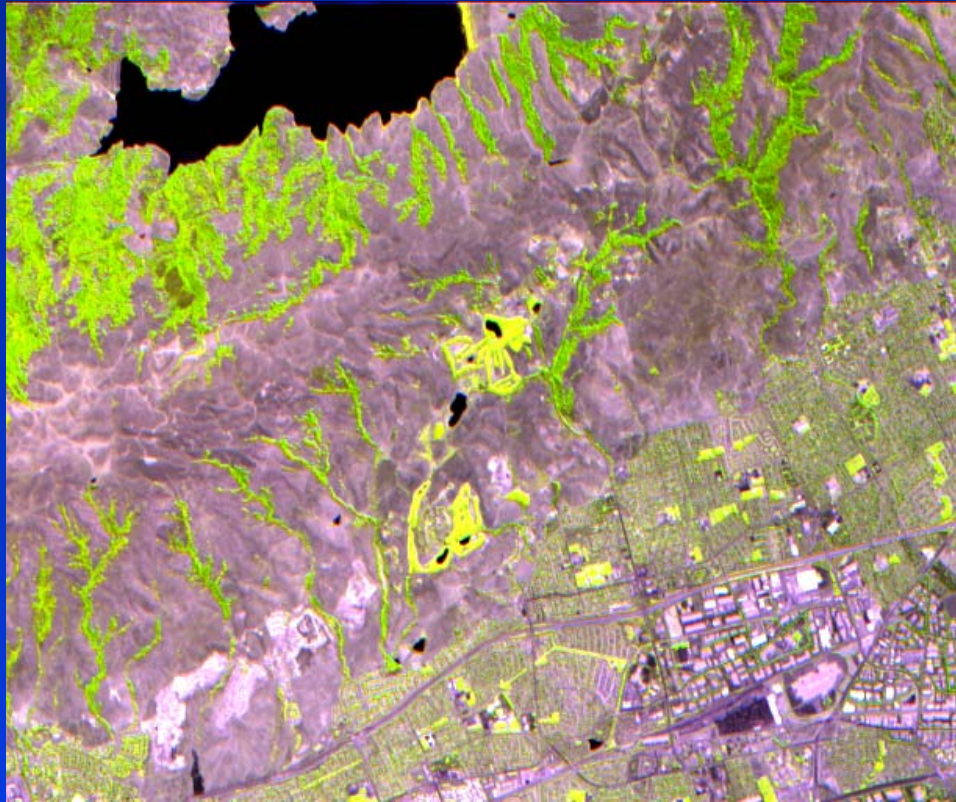
# GENIE Classification

- Correctly classified pixels are green (or red) pixels that match on both training data and output. Green points in the training data mapped to red or red points in the training data mapped to green are incorrectly classified.

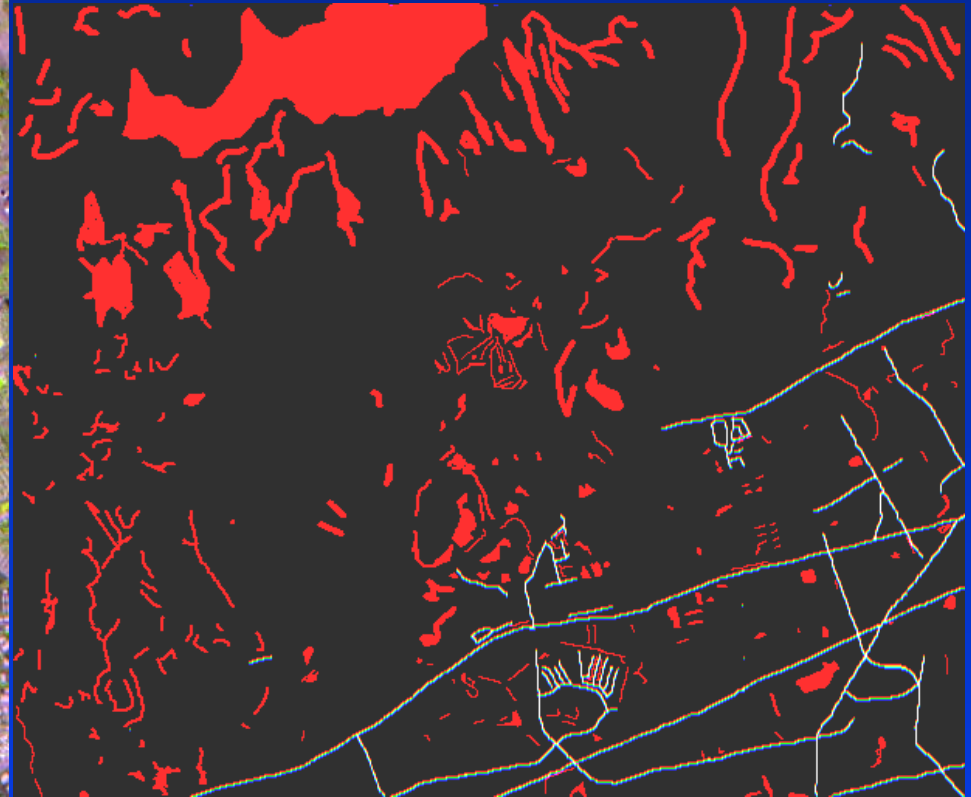


# Moffet Field.

- Source image.

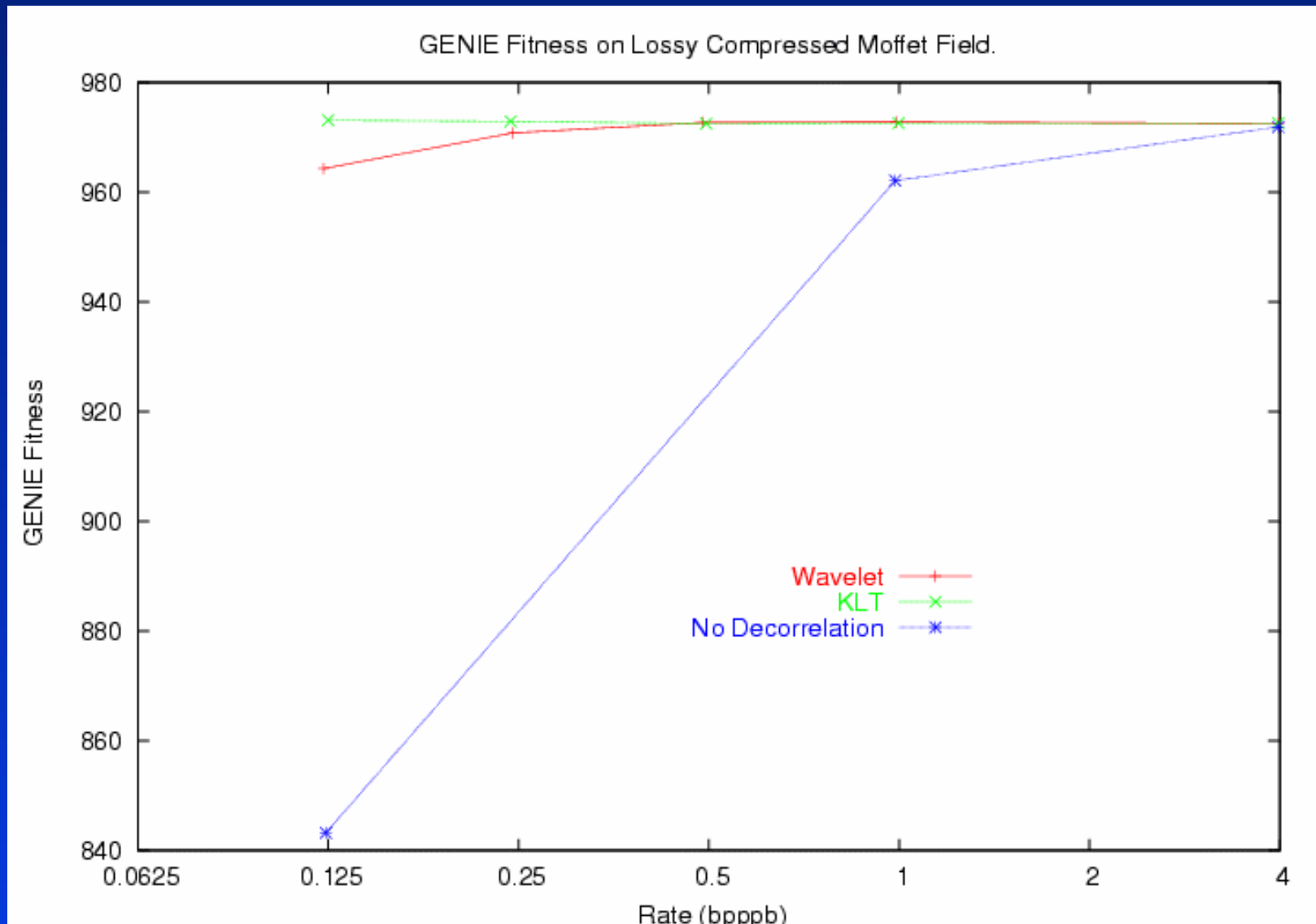


- Training classes. White: asphalt-like; Red: highly different from asphalt.





# Moffet Field. GENIE fitness for “road” class.



# Conclusions

- The experiments demonstrate that all of the classification tasks investigated are robust with respect to lossy compression of the source image. The percentage of correctly classified points converges to 100% at rates of around 4 bpppb. GENIE classification results are consistent with the results from the other classifiers examined.
- Component decorrelation significantly improves the classification of compressed/reconstructed data. To get 99.9% of the pixels classified correctly, a rate of at least 1 bpppb is necessary in experiments without component decorrelation, whereas with KLT decorrelation this success rate is achieved at 0.25 to 0.5 bpppb.
- Classification of KLT-decorrelated images is more accurate than classification of wavelet-decorrelated images. However, the cost of KLT decorrelation is significant: on average it takes 4 times more CPU time to compress/reconstruct images with KLT than with wavelet decorrelation: 120 minutes for KLT and 30 minutes for wavelets.